

ec 10 Math 343

$$\vec{y} = X\vec{\beta} + \vec{\epsilon}$$

$$\vec{\epsilon} \sim N_n(\vec{0}, \sigma^2 I_n)$$

$$\Rightarrow \epsilon_1, \dots, \epsilon_n \text{ iid } N(0, 1)$$

Obp for mispec error + ignore em

$$\vec{y} = X\vec{\beta} + \vec{\epsilon}$$

Assume

random through  $\vec{\epsilon}$   
fixed covariates  
unknown parameter

$$\vec{\beta} = (X^T X)^{-1} X^T \vec{y} \sim N_{p+1}(\vec{\beta}, \sigma^2 (X^T X)^{-1}) \Rightarrow \beta_j \sim N(\beta_j, \sigma^2 (X^T X)^{-1}_{jj})$$

$$\Rightarrow \frac{\beta_j - \hat{\beta}_j}{\sigma \sqrt{(X^T X)^{-1}_{jj}}} \sim N(0, 1) \quad \forall j$$

But  $\sigma$  is unknown!

$$\Rightarrow \vec{y} = X\vec{\beta}$$

$$\vec{y} = X\vec{\beta} + \vec{\epsilon} = \hat{\vec{y}} + \vec{\epsilon}$$

Obp for  $\vec{\epsilon}$ , the residuals in the regression

Left over from lec 9:

$$\Rightarrow \vec{\epsilon} = \vec{y} - X\vec{\beta} = \underbrace{(I - H)}_{\text{geometrically}} \vec{y} = \underbrace{(I - H)(X\vec{\beta} + \vec{\epsilon})}_{\vec{0}_{(p+1) \times (p+1)}} = (I - H)X\vec{\beta} + (I - H)\vec{\epsilon}$$

$$= (I - H)\vec{\epsilon} \sim N_n(\vec{0}, (I - H)\sigma^2 I_n(I - H)^T) = N_n(\vec{0}, \sigma^2(I - H))$$

$$\Rightarrow \epsilon_i \sim N(0, \sigma^2(1 - H_{ii}))$$

From Math 340:  $\vec{U} \sim N_n(\vec{0}, I_n)$ ,  $\vec{A} \in \mathbb{R}^{n \times n} \Rightarrow \vec{A}\vec{U} \sim N_n(\vec{0}, \vec{A}\vec{A}^T)$

$$\vec{y} = X\vec{\beta} = H\vec{y} = H(X\vec{\beta} + \vec{\epsilon}) = HX\vec{\beta} + H\vec{\epsilon} = X\vec{\beta} + H\vec{\epsilon} \sim N_n(X\vec{\beta}, H\sigma^2 I_n) = N_n(X\vec{\beta}, \sigma^2 H) \Rightarrow \hat{\vec{y}}_i \sim N(\hat{y}_i, \sigma^2 H_{ii})$$

In 340 we showed that if  $\vec{z} \sim N_n(\vec{0}, \sigma^2 I_n)$

$$\Rightarrow \vec{z}^T \vec{z} \sim \chi^2_n$$

From last class:

$$\vec{z}^T \vec{z} = \underbrace{\frac{1}{\sigma^2} \vec{z}^T H \vec{z}}_{B_1} + \underbrace{\frac{1}{\sigma^2} \vec{z}^T (I - H) \vec{z}}_{B_2}$$

Since  $B_1 + B_2 = I_n$  and  $\text{rank}(B_1) + \text{rank}(B_2) = (p+1) + (n - (p+1)) = n$ , we can use Cochran's thm

$$\Rightarrow \frac{1}{\sigma^2} \vec{z}^T H \vec{z} \sim \chi^2_{p+1} \text{ indep of } \frac{1}{\sigma^2} \vec{z}^T (I - H) \vec{z} \sim \chi^2_{n - (p+1)}$$

least-squares      normal || error

$$\frac{1}{\sigma^2} \vec{\varepsilon}^T (\mathbf{I} - \mathbf{H}) \vec{\varepsilon} = \dots = \frac{1}{\sigma^2} \|\vec{\varepsilon}\|^2 \sim \chi^2_{n-(p+1)}$$

$$\begin{aligned} \frac{1}{\sigma^2} \vec{\varepsilon}^T \mathbf{H} \vec{\varepsilon} &= \frac{1}{\sigma^2} \vec{\varepsilon}^T \mathbf{H} \mathbf{H} \vec{\varepsilon} = \frac{1}{\sigma^2} \vec{\varepsilon}^T \mathbf{H}^T \mathbf{H} \vec{\varepsilon} = \frac{1}{\sigma^2} (\mathbf{H} \vec{\varepsilon})^T (\mathbf{H} \vec{\varepsilon}) = \frac{1}{\sigma^2} \|\mathbf{H} \vec{\varepsilon}\|^2 \\ &= \frac{1}{\sigma^2} \|\mathbf{H}(\vec{y} - \mathbf{X}\vec{\beta})\|^2 = \frac{1}{\sigma^2} \|\mathbf{H}\vec{y} - \mathbf{H}\mathbf{X}\vec{\beta}\|^2 = \frac{1}{\sigma^2} \|\vec{y} - \mathbf{X}\vec{\beta}\|^2 \\ &= \frac{1}{\sigma^2} \|\underbrace{\mathbf{X}\vec{\beta}}_{\vec{y}} - \underbrace{\mathbf{X}\vec{\beta}}_{\vec{y}}\|^2 = \frac{1}{\sigma^2} \|\mathbf{X}(\vec{\beta} - \vec{\beta})\|^2 \sim \chi^2_{p+1} \end{aligned}$$

normal estimation error

$$\text{As } n \rightarrow \infty \quad \vec{\varepsilon} \rightarrow \vec{\varepsilon}, \quad \vec{\beta} \rightarrow \vec{\beta} \Rightarrow \|\mathbf{X}(\vec{\beta} - \vec{\beta})\|^2 \rightarrow 0$$

independent + ignore error      common error disappears

$\Rightarrow \vec{\varepsilon}$  and  $\vec{\beta}$  are independent  $\Rightarrow \|\vec{\varepsilon}\|^2$  and  $\vec{\beta}$  are independent

Consider the following statistic

from least-squares

$$\frac{\frac{b_j - \beta_j}{\sigma \sqrt{(\mathbf{X}^T \mathbf{X})^{-1}_{jj}}}}{\sqrt{\frac{\frac{1}{\sigma^2} \|\vec{\varepsilon}\|^2}{n-(p+1)}}} \sim T_{n-(p+1)} \quad \text{Student's } T \text{ test}$$

indep.      we just proved this

$$= \frac{\frac{b_j - \beta_j}{\sigma \sqrt{(\mathbf{X}^T \mathbf{X})^{-1}_{jj}}}}{\frac{1}{\sigma} \sqrt{\frac{\|\vec{\varepsilon}\|^2}{n-(p+1)}}} \sim T_{n-(p+1)}$$

estimate  
the test statistic is then

$$\frac{b_j - \beta_j}{\sqrt{(\mathbf{X}^T \mathbf{X})^{-1}_{jj}}} \quad b_j - \beta_j$$

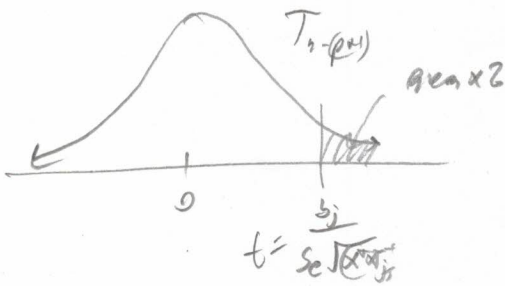
Assume level of test is  $\alpha$ .  
 Usually the inference is for  $H_0: \beta_j = 0 \Leftrightarrow H_1: \beta_j \neq 0$  why?  
 Usually the inference is for  $H_0: \beta_j = 0 \Leftrightarrow H_1: \beta_j \neq 0$  why?  
 Because if  $\beta_j = 0$ , the job feature doesn't affect the response (nearly)  
 (which usually means the overall relationship is not too interesting).

In this case,

$$\frac{\hat{\beta}_j}{\text{se}(\hat{\beta}_j)} \in \left[ -t_{1-\frac{\alpha}{2}, n-p-1}, t_{1-\frac{\alpha}{2}, n-p-1} \right]$$

Interpreting the test  $\Rightarrow$   $CI_{\beta_j, 1-\alpha} = \left[ \hat{\beta}_j \pm t_{1-\frac{\alpha}{2}, n-p-1} \cdot \text{se}(\hat{\beta}_j) \right]$

How to get p-value?



p-value =  $2P(|T_{n-p-1}| > \left| \frac{\hat{\beta}_j}{\text{se}(\hat{\beta}_j)} \right|)$

Consider a new  $\vec{x}_*$  and you want to predict its expected response of many predictions of  $\vec{x}_*$  since the noise mean is zero.  
 $h^*(\vec{x}_*) = \vec{x}_* \vec{\beta}$ . This is the average  
 let  $\mu_* := \vec{x}_* \vec{\beta}$

$$\hat{Y}_* = \vec{x}_* \vec{B} \Rightarrow \hat{Y}_* \sim N(\underbrace{\vec{x}_* \vec{\beta}}_{\mu_*}, \sigma^2 \vec{x}_* (X^T X)^{-1} \vec{x}_*^T)$$

$$\vec{B} \sim N(\vec{\beta}, \sigma^2 (X^T X)^{-1}) \Rightarrow \frac{\hat{Y}_* - \mu_*}{\sigma \sqrt{\vec{x}_* (X^T X)^{-1} \vec{x}_*^T}} \sim N(0, 1)$$

Again,  $\sigma$  is unknown so consider

$$\frac{\hat{Y}_* - \mu_*}{\sigma \sqrt{\vec{x}_* (X^T X)^{-1} \vec{x}_*^T}} \sim N(0, 1) \quad \text{since } \hat{Y}_* \text{ is a function of } \vec{B}.$$

$$\downarrow \text{ indep.}$$

$$\frac{\hat{Y}_* - \mu_*}{\sqrt{\frac{\frac{1}{2} \|\vec{E}\|^2}{n - (p+1)}}} \sim T_{n - (p+1)}$$

$$\frac{\hat{Y}_* - \mu_*}{\sqrt{\vec{x}_* (X^T X)^{-1} \vec{x}_*^T}} \cdot \frac{\sqrt{\frac{1}{2} \|\vec{E}\|^2}}{\sqrt{n - (p+1)}} \sim T_{n - (p+1)}$$

the test statistic for  $H_0: \mu_* = 0$  is

$$T = \frac{\hat{Y}_* - 0}{s_e \sqrt{\vec{x}_* (X^T X)^{-1} \vec{x}_*^T}} \in [\pm t_{1-\frac{\alpha}{2}, n - (p+1)}] \Rightarrow \text{Reject}$$

which can be used to test. Inverting the test yields

$$CI_{\mu_*} = \left[ \hat{Y}_* \pm t_{1-\frac{\alpha}{2}, n - (p+1)} \cdot s_e \sqrt{\vec{x}_* (X^T X)^{-1} \vec{x}_*^T} \right]$$